# THE NEIGHBORHOOD CONTEXT OF RACIAL AND ETHNIC DISPARITIES IN ARREST*

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*This study assesses the role of social context in explaining racial and ethnic disparities in arrest, with a focus on how distinct neighborhood contexts in which different racial and ethnic groups reside explain variations in criminal outcomes. To do so, I utilize a multilevel, longitudinal research design, combining individual-level data with contextual data from the Project on Human Development in Chicago Neighborhoods (PHDCN). Findings reveal that black youths face multiple layers of disadvantage relative to other racial and ethnic groups, and these layers work to create differences in arrest. At the family level, results show that disadvantages in the form of unstable family structures explain much of the disparities in arrest across race and ethnicity. At the neighborhood level, black youths tend to reside in areas with both significantly higher levels of concentrated poverty than other youths as well as lower levels of collective efficacy than white youths. Variations in neighborhood tolerance of deviance across groups explain little of the arrest disparities, yet tolerance of deviance does influence the frequency with which a crime ultimately ends in an arrest. Even after accounting for relevant demographic, family, and neighborhood-level predictors, substantial residual arrest differences remain between black youths and youths of other racial and ethnic groups.*

Two competing explanations have long been posited to explain the fact that black individuals are drastically overrepresented in the criminal justice system: (1) differences in the prevalence and incidence of criminal offending across racial and ethnic groups account for arrest disparities (see, e.g., Hindelang 1978), or (2) the criminal justice system discriminates against certain groups (see, e.g., Chambliss and Nagasawa 1969). However, these diametric explanations for arrest disparities prove to be too simplistic in reality. This paper explores a more nuanced argument, contending that the apparent correlation between individual race/ethnicity and arrest is actually confounded with social context. Youths of different racial and ethnic groups often reside in substantially different neighborhood and family contexts, and the difference in contexts ultimately influences disparities in criminal outcomes across groups. Although the empirical literature demonstrates that neighborhood-level factors (such as concentrated poverty) influence racial and ethnic disparities in crime (McNulty and Bellair 2003; Sampson, Morenoff, and Raudenbush 2005), there is less evidence for why. For example, the extent to which neighborhood conditions shape norms governing criminal behavior as well as whether variation in norms across race and ethnicity explains differences in arrest is unclear.

I examine three central questions in this study. First, do youths from different racial and ethnic groups, residing in the same neighborhood, have differing likelihoods of arrest?

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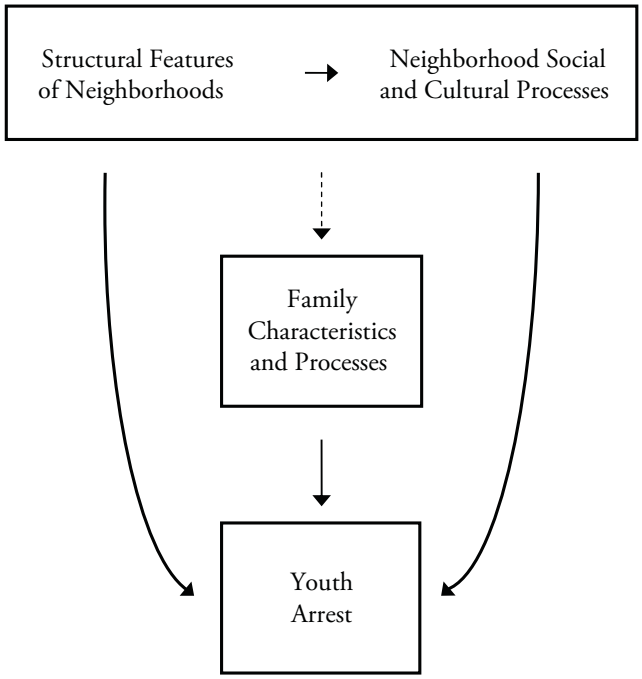
**Figure 1. Conceptual Framework**




Second, do youths of similar race and ethnicity who reside in different neighborhood contexts have differing likelihoods of being arrested, even given similar levels of offending? Third, then if so, which particular aspects of neighborhood environments contribute to disparities in arrest? The explanation could be that police arrest members of certain racial and ethnic groups more often because they commit more crimes, and also because certain groups tend to reside in neighborhoods where the probability of a crime leading to an arrest is higher.

## CONCEPTUAL FRAMEWORK

Figure 1 depicts the conceptual framework that serves as a guide for answering the preceding questions. This framework presents at a high level how neighborhoods directly and indirectly influence the outcome of arrest.[1]

### Neighborhood Structure and Social and Cultural Processes

To operationalize the framework depicted in Figure 1, I borrow from social disorganization theory (Shaw and McKay 1942) and recent work in this tradition. While the most commonly studied aspect of Shaw and McKay's social disorganization model is the association between neighborhood structural characteristics (i.e., economic status, ethnic heterogeneity, and residential mobility) and delinquency, the part of their empirical work that serves as the foundation for discussions of racial and ethnic differences in crime is their observation that the geographic concentration of delinquency persisted in the same areas of Chicago

1. Critics may note the absence of certain associations in this figure. For instance, it is reasonable to argue that the model should instead be nonrecursive, with youth arrests influencing family and neighborhood factors. However, this framework is specified as such to focus on the key pathways by which neighborhoods influence arrest.

over a 40-year period (1900–1940). This concentration of delinquency persisted despite substantial population turnover in delinquent areas, including the turnover from one ethnic group to another. This finding led Shaw and McKay to conclude that regardless of changes in the racial and ethnic composition of Chicago neighborhoods, the relative distribution of delinquency throughout the city would remain stable over time. Specifically referring to violence, Sampson and Wilson (1995:41) built upon these arguments set forth by Shaw and McKay, arguing, "[T]he sources of violent crime appear to be remarkably invariant across race and rooted instead in the structural differences among communities, cities, and states in economic and family organization."

In a recent review of the literature concerning race, ethnicity, and crime, Peterson and Krivo (2005) called for research on neighborhood mechanisms and social processes that explain why structural features (such as poverty) are associated with crime and why certain social groups are more likely to engage in crime. One mechanism of importance in the social disorganization model is social control, including variants such as collective efficacy. According to Sampson, Raudenbush, and Earls (1997), neighborhood poverty and disadvantage undermine the capacity of residents and families to engage in the social control of criminal behavior.

Another mechanism that explains the relation between neighborhood structure and crime is neighborhood cultural norms. Sampson and Wilson (1995) contended that neighborhood context shapes norms for expected behavior and that social disorganization can lead to the emergence of ecologically structured norms that tolerate lawlessness. Sampson and Wilson did not deny that a distinctive subculture exists in socially isolated and disorganized neighborhoods, but this subculture varies with the structural features of neighborhoods.

Sampson and Bartusch (1998) found support for the argument that neighborhood conditions shape norms governing the behavior of youths. Specifically, concentrated disadvantage is a positive predictor of the extent to which neighborhood residents tolerate deviant behavior of youths, and this relationship holds when adjusting for the demographic characteristics of residents. Thus, tolerance of deviance is influenced by neighborhood conditions and emerges as a property of neighborhoods rather than as a sole attribute of individual residents. Ethnographic research (see, e.g., Anderson 1999) provides support for the argument that neighborhoods characterized by concentrated disadvantage and social isolation give rise to cultural adaptations that tolerate or legitimize criminal and violent behavior (i.e., "the code of the street"), but little quantitative work has explored this argument (for an exception, see Matsueda, Drakulich, and Kubrin 2006). Thus, this paper attempts to answer whether cultural adaptations to neighborhood conditions, in the form of tolerance of deviance, necessarily translate into higher rates of arrest.

The preceding discussion suggests that variation across racial and ethnic groups with respect to the structural features of neighborhoods (see Figure 1) may explain group differences in arrest. Furthermore, these structural features may influence neighborhood social and cultural processes (also see Figure 1), such as tolerance of deviance as well as collective efficacy. In turn, these processes are associated with arrest. In sum, racial and ethnic disparities in crime may result because groups tend to live in vastly different neighborhood contexts and because these contexts shape norms for expected behavior.

## Family Characteristics and Processes

By numerous pathways, family factors influence all types of youth behavior and outcomes of that behavior, such as arrest. (For comprehensive reviews, see Burton and Jarrett 2000; Loeber and Stouthamer-Loeber 1986; Wells and Rankin 1991.) Family structural characteristics, such as socioeconomic status (Duncan and Brooks-Gunn 1997; Duncan, Brooks-Gunn, and Klebanov 1994), marital status (McLeod, Kruttschnitt, and Dornfeld 1994; Wells and Rankin 1991), household size and composition (Sampson and Laub 1993), and family disruption (Sampson 1987), have been linked to youth problem behavior. The fundamental

issue to understand is why these family characteristics influence behavior. Research has shown that family structural characteristics, such as those outlined earlier, influence youths' behavior because they affect family processes (e.g., supervision and discipline) as well as parent-child conflict and child attachment to parents (Loeber and Stouthamer-Loeber 1986; Sampson and Laub 1993). Related to Figure 1, family structural characteristics influence family processes, such as socialization of youths and the capability of families to control the behavior of youths. In the absence of social control, problem behavior and crime become more likely.

It is critical to note that neighborhood context influences both family structure and processes, which in turn influence youths' behavior. Thus, family factors mediate and moderate the effects of neighborhood context on youths' behavior (Duncan and Raudenbush 2001), which is denoted by the dashed-line arrow in Figure 1. However, it is beyond the scope of this study to test all relevant intervening relationships, so only direct effects of neighborhood characteristics will be estimated, as follows.

## HYPOTHESES

Clearly, a large number of contextual factors potentially explain the correlation between race/ethnicity and arrest. This study combines family and neighborhood factors into a single analytical framework to investigate the influence of each on the likelihood of arrest, examining whether these factors explain racial and ethnic disparities in arrest. Importantly, this study moves beyond the typical black-white comparison of crime differences by examining arrest differences across ethnicity and immigration status, in addition to race. Given the ethnic diversity of American society, particularly in urban areas, it is vital to consider whether social context explains arrest disparities across all types of demographic groupings. At the neighborhood level, this study examines whether the law is more likely to be invoked in one neighborhood versus another, given that not all crimes lead to an arrest. The foregoing discussions lead to three hypotheses that the present study explores. First, I hypothesize that concentrated poverty and the percentage of foreign-born residents in a neighborhood are positively associated with arrest, and that residential stability is negatively associated with arrest. Furthermore, differences in these neighborhood structural features across race and ethnicity explain portions of the racial and ethnic disparities in arrest.

Second, collective efficacy is negatively associated with arrest, and tolerance of deviance is positively associated with arrest. Moreover, these neighborhood social and cultural processes account for part of the associations between neighborhood structural features and arrest.

Third, family factors—such as socioeconomic status, parental marital status, household size and composition, and social control—are associated with arrest; and these family factors account for part of the association between neighborhood factors and arrest.

## DATA AND RESEARCH DESIGN

The study sample is drawn from the PHDCN, a multiwave study of the factors influencing human development and antisocial behavior of Chicago youth. The PHDCN collected longitudinal data on seven cohorts of subjects, defined by age at baseline (0, 3, 6, 9, 12, 15, and 18 years old), with subjects and their primary caregivers interviewed three times between 1995 and 2002. This paper focuses on the 12-, 15-, and 18-year-old age cohorts. For the data collection, the PHDCN selected a random sample of 80 neighborhood clusters, stratified by racial/ethnic composition (seven categories) and socioeconomic status (high, medium, and low), from a total of 343 neighborhood clusters in Chicago (Sampson et al. 1997). Within these 80 neighborhoods, a simple random sample of households yielded a total sample of 2,150 youths in the 12-, 15-, and 18-year-old cohorts. The present analysis uses a subset of the total sample ($N = 1,775$) who consented to have their official criminal records searched. This subsample showed no significant difference in the average number of self-reported

arrests per wave compared with youth subjects who did not consent to a criminal records search ($F = 0.975$; $df = 1, 2149$). See Table A1 in the Appendix for further comparison of the analytic sample to those subjects who did not consent to a records search.

## Dependent Variable

The Chicago Police Department and the Illinois State Police provided official arrest data on juveniles and adults, which cover the time span from 1995 to 2001.[2] The dependent variable derived from these data is the frequency of arrest per person-year. I construct person-year observations by calculating the age of a given subject as of January 1 of a given year, and then by summing the count of arrests over the subsequent 12-month period.

## Independent Variables

The statistical models include a number of individual-, family-, and neighborhood-level predictors. Key individual demographic factors include age, cohort, and gender. Further, the analyses employ five dummy indicators of race and ethnicity: black, Mexican, other Latino, other race, and white. Black, white, and other race groups are all non-Latino. In analyses to follow, the black dummy variable is used as the reference category. Also, the race and ethnicity dummy variables are aggregated to the neighborhood-level to produce indicators of the percent racial and ethnic composition of each given neighborhood.

Given arguments from other research that arrest disparities across racial and ethnic groups are largely due to differential involvement in offending (Hindelang 1978), a key individual-level explanatory variable to examine is the role of self-reported criminal offending. Analyses include a measure of offending, created from a total of 17 survey items from the Wave 1 self-report survey. These items are indicators of the frequency of violent, property, and drug offenses occurring over the 12-month period preceding the survey date. I combine all items into a scale, using an ordinal item response model (IRT) with the STATA GLLAMM program (Rabe-Hesketh, Skrondal, and Pickles 2004). IRT is a measurement strategy that, in the present case, posits that individuals' responses to self-report offending items are a function of both their latent propensity toward offending and the severity of the crime (see Osgood, McMorris, and Potenza 2002). The latent propensity scores obtained from an IRT model approximate the normal distribution, thus remedying the problem of skewness associated with rare events, such as certain crimes.

The study includes six measures of family characteristics as predictors of arrest: socioeconomic status, family structure, presence of extended adult kin, number of household children, immigrant generational status (first, second, or third and higher), and family control. Socioeconomic status is a composite measure of the primary caregiver's education, occupation, and income. A binary variable, reflecting the marital status of a youth's biological parents, describes family structure. The measure of family control derives from caregiver responses to the Family Environment Scales survey instrument (Moos and Moss 1986), measuring the extent to which strict rules for behavior as well as a hierarchy for decision-making characterize the family.

Three measures capture characteristics of neighborhood structure: concentrated poverty, residential stability, and the percentage of foreign-born residents. Each measure derives from 1990 U.S. census data. Scales were created via factor analyses, with items weighted by their factor loadings. Concentrated poverty refers to a scale of economic disadvantage. I use the following census indicators to construct the measure: percentages of families with income below the poverty line, of families receiving public assistance,

2. Both official crime data and self-report data have known limitations, so readers may question whether inferences about the relation between crime and measures of social context are dependent upon the data source. Fortunately, previous research using the same sample of PHDCN youth revealed that the neighborhood-level and family-level predictors of arrest are largely invariant across data source (Kirk 2006).

of unemployed individuals in the civilian labor force, and of female-headed families with children. Residential stability derives from the following census indicators: the percentage of residents 5 years old and older who lived in the same house five years earlier, and the percentage of homes that are owner-occupied.

To test arguments about the influence of neighborhood social and cultural processes on arrest, statistical models include measures of neighborhood tolerance of deviance and collective efficacy, which derive from the 1995 PHDCN Community Survey. The Community Survey yielded a probability sample of 8,782 Chicago residents and was collected on a sample independent of the longitudinal cohort data collection described earlier. Four items are used to construct the tolerance of deviance scale, which concern "how wrong" it is for a 13-year-old to (1) smoke cigarettes, (2) use marijuana, (3) drink alcohol, and (4) get into fist fights. Higher scores equate to higher levels of tolerance for these behaviors (i.e., the belief that these behaviors are not wrong). The measure of collective efficacy is identical to the scale developed by Sampson et al. (1997) and represents a combined measure of neighborhood social control as well as social cohesion and trust. Neighborhood social control refers to the willingness of residents to intervene in the following situations: if (1) children were skipping school and hanging out on a street corner, (2) children were spray painting graffiti on a local building, (3) children were showing disrespect to an adult, (4) a fight broke out, and (5) the fire station closest to the respondent's home was threatened with budget cuts. The measure of social cohesion and trust is based on the level of respondent agreement to the following statements: (1) People around here are willing to help their neighbors; (2) People in this neighborhood can be trusted; (3) People in this neighborhood generally get along with each other; (4) This is a close-knit neighborhood; and (5) People in this neighborhood share the same values. Both scales were constructed via a multilevel regression model, with responses to each survey question nested within a respondent, and respondents nested within neighborhoods.

## ANALYTIC STRATEGY AND STATISTICAL MODELS

Analyses of the racial and ethnic disparities in arrest follow two paths: (1) growth curve analyses of all arrests estimated by population-averaged age-arrest trajectories, and (2) a decomposition of racial and ethnic differences in arrest trajectories into differences in group attributes and differences in the size and direction of regression coefficients across groups.

### Growth Curves

In the first approach, I specify a series of quadratic growth models with arrest as the dependent variable. With a quadratic growth curve, I model an individual's change (or growth) in arrest over time as a function of their age and a squared age term. The baseline model in this study also includes individual-level demographic indicators of cohort, gender, race, and ethnicity.

In the analyses, age is centered at 17. I choose this age because it provides an overlap in the observation periods for all cohorts: age 17 is the end of the observation period for the 12-year-old cohort and also the beginning of the observation period for the 18-year-old cohort. With this centering, I use model coefficients to assess the expected count of arrests at age 17 and the rate of change in arrest at age 17. I first expand the baseline model with the addition of indicators of neighborhood racial and ethnic composition, followed by the inclusion of additional neighborhood predictors and family-level predictors. By including neighborhood indicators in the model prior to adjusting for the effects of relevant family-level predictors, I seek to identify the likely upper bounds of neighborhood effects on arrest. After adjusting for family-level covariates, there may be little direct effect of neighborhoods on arrest. Family and parental processes are often influenced by neighborhood context (Burton and Jarrett 2000), so the addition of family variables to

statistical models may result in findings of little direct neighborhood effects, yet substantial indirect effects.

Each model in the analysis assumes that $Y_{tjk}$, which is the observed number of official police arrests for person $j$ in neighborhood $k$ at age $t$, follows a Poisson distribution. I structure the data such that each observation represents one person-year, with a total of $t$ observations per person $j$. With the Poisson distribution, the conditional mean and variance are assumed to be equal, although this may not be true with arrest data. Thus, I add a dispersion parameter to all models to allow for conditional variance that is larger or smaller than expected.

Eq. (1) specifies the growth curve model:

$$\log E(Y_{tjk}) = \pi_{0jk} + \pi_{1jk}(AGE - 17)_{tjk} + \pi_{2jk}(AGE - 17)^2_{tjk}. \quad (1)$$

Eq. (2) shows that the expected count of arrests at age 17 is modeled as a function of individual, family, and neighborhood covariates, where $\mathbf{X_{jk}\beta}$ is a vector of individual and family characteristics and $\mathbf{W_k\gamma}$ is a vector of neighborhood characteristics:

$$\pi_{0jk} = \mu + \mathbf{X_{jk}\beta} + \mathbf{W_k\gamma}. \quad (2)$$

All covariates are centered on their grand means; thus, model coefficients can be interpreted as the average effect or association across neighborhoods. Further, because the demographic dummy variables (i.e., race, ethnicity, gender, and cohort) are centered on their grand means, the intercept is interpreted as the expected number of arrests by the *average* youth, not the expected count for the dummy reference categories. With these models, the expected count of arrests at a particular age is given by Eq. (3):

$$E\left(\mathbf{Y}_{tjk}\right) = \left(\mathbf{x}'_{jk}\boldsymbol{\beta} + \mathbf{w}'_{k}\boldsymbol{\gamma}\right). \quad (3)$$

## Decomposition of Racial and Ethnic Differences

Using a nonlinear variant of the Blinder-Oaxaca decomposition methodology (Blinder 1973; Oaxaca 1973), in the second stage of analysis, I partition the arrest gap between racial and ethnic groups into differences attributable to differing attributes of each group as well as differences in the size and direction of the regression coefficients across groups. As an example of the former, if arrest is inversely related to family socioeconomic status, I isolate exactly how much of the gaps in arrest between racial and ethnic groups are attributable to differences in socioeconomic status across groups. However, residual group differences will likely remain after accounting for observed group attributes. When separate growth curves are estimated across racial and ethnic groups, residual differences in arrest will be reflected in differences in the size of the intercept across equations and in differences in the slope coefficients of explanatory variables. Differences in the slope coefficients can be interpreted to mean that the strength of association between arrest and key correlates of arrest differs across groups, whereas differences in the intercept represent the unexplained portion of the difference that may be due to unobserved differences across groups (Jones and Kelley 1984).

To demonstrate the technique, I use a decomposition of black-white differences in arrest as an example. With a linear regression model, the difference in the mean values of a dependent variable across groups can be partitioned into differences in attributes and differences in ordinary least squares coefficients, as follows in Eq. (4):

$$\bar{Y}_{Black} - \bar{Y}_{White} = \left[\left(\bar{X}_B - \bar{X}_W\right)\beta_B\right] + \left[\bar{X}_W\left(\beta_B - \beta_W\right)\right]. \quad (4)$$

With respect to arrest differences, the first term on the right side of Eq. (4) can be used to assess how much the expected arrest count for black subjects would change if they had similar attributes as white subjects, with the associations between attributes and arrest still determined with black coefficients. The second term can be used to assess how much of the arrest gap is attributable to how the association between arrest and relevant correlates of arrest differs across groups.[3]

Of course, in a linear regression model, an identity link function is used to linearize the expected value of a given dependent variable. Yet, with a Poisson model, a log link function is used to transform the dependent variable. Consequently, the conventional Blinder-Oaxaca decomposition method, which assumes $E(\mathbf{Y}_{tjk}) = (\mathbf{x}'_{jk}\boldsymbol{\beta} + \mathbf{w}'_{k}\boldsymbol{\gamma})$, is not appropriate with nonlinear functions. Following Yun (2004), I utilize a more general variant of the Blinder-Oaxaca method in Eq. (4) that is applicable when using count data and a Poisson regression model.

For the first step of the decomposition, I estimate group-specific regressions similar to the growth curve model described in Eqs. (1) and (2). With group-specific coefficients and means, I then compute the difference in the expected count of arrest at age 17 with the following equation:

$$\bar{Y}_{Black} - \bar{Y}_{White} = \sum_{i=1}^{i=K} W^{i}_{\Delta X}\left[F\left(X_B\beta_B\right) - F\left(X_W\beta_B\right)\right] + \sum_{i=1}^{i=K} W^{i}_{\Delta\beta}\left[F\left(X_W\beta_B\right) - F\left(X_W\beta_W\right)\right], \quad (5)$$

where $W^{i}_{\Delta X}$ is a weight reflecting the contribution of each given variable to the total group differences in the dependent variable due to attributes, and $W^{i}_{\Delta\beta}$ is a coefficient weight reflecting the contribution of each variable to group differences due to coefficients. These weights are given by Eq. (6):

$$W^{i}_{\Delta X} = \frac{\left(\bar{X}^{i}_{B} - \bar{X}^{i}_{W}\right)\beta^{i}_{B}}{\left(\bar{X}_{B} - \bar{X}_{W}\right)\beta_{B}} \text{ and } W^{i}_{\Delta\beta} = \frac{\bar{X}^{i}_{W}\left(\beta^{i}_{B} - \beta^{i}_{W}\right)}{\bar{X}_{W}\left(\beta_{B} - \beta_{W}\right)}, \quad (6)$$

where $\sum_{i=1}^{i=K} W^{i}_{\Delta X} = \sum_{i=1}^{i=K} W^{i}_{\Delta\beta} = 1$.

In analyses to follow, I not only report the aggregate differences in arrest across racial and ethnic groups attributable to differing attributes and coefficients but I also isolate the influence of particular attributes on group differences in arrest. Finally, I report a series of hypothetical growth curves that illustrate the predicted trajectories of arrest for black youths if the attributes between black and white subjects were equalized.

## RESULTS

A total of 334 PHDCN subjects from the 12-, 15-, and 18-year-old cohorts (19% of the sample) were arrested at least once from 1995 to 2001. Of this number, 148 were arrested one time (8.3%), and the remainder were arrested at least twice. A total of 1,057 arrests of the PHDCN youths were officially recorded in Illinois from 1995 to 2001. Of these 1,057 arrests, 221 arrests were for violent offenses, 233 for property offenses, 301 for offenses against the public order, 272 for drug offenses, and 30 for other offenses (including warrants and unclassified arrests).

3. An alternative decomposition can be performed that simply switches the comparison group: that is, differences in group attributes are valued with white coefficients, and differences in coefficients are valued with black attributes (see Jones and Kelley 1984):

$$\bar{Y}_{Black} - \bar{Y}_{White} = \left[\left(\bar{X}_B - \bar{X}_W\right)\beta_W\right] + \left[\bar{X}_B\left(\beta_B - \beta_W\right)\right].$$

**Table 1. Arrest Summary by Race/Ethnicity: PHDCN Waves 1–3, Cohorts 12–18 (*N* = 1,775)**

| Variable | Black (*N* = 641) | Mexican (*N* = 560) | Other Latino (*N* = 227) | Other Race (*N* = 68) | White (*N* = 279) |
|---|---|---|---|---|---|
| Number of Arrestees | 188 | 71 | 32 | 9 | 34 |
| % of Total *N* | 29.3 | 12.7 | 14.1 | 12.0 | 12.2 |
| Number of Arrests | 636 | 218 | 86 | 20 | 97 |
| Violent | 144 | 45 | 13 | 4 | 15 |
| Property | 110 | 54 | 33 | 2 | 34 |
| Public order | 201 | 48 | 21 | 6 | 25 |
| Drug | 161 | 66 | 19 | 5 | 21 |
| Other offense | 20 | 5 | 0 | 3 | 2 |
| Mean Number of Arrests All Years (arrestees) | 3.4 | 3.1 | 2.7 | 2.2 | 2.9 |
| Mean Number of Arrests, All Years (total *N*) | 1.0 | 0.4 | 0.4 | 0.3 | 0.3 |

*Note:* Arrest counts by offense type based on most serious offense classification, for those arrests with multiple charges.

Table 1 displays a descriptive summary of arrests by race and ethnicity. Here, it can be seen that a much greater percentage of black youths in the sample were arrested than the other racial and ethnic groups (almost 30% of black youths, compared with roughly 12%–14% of the other groups). Because of this, blacks have a mean number of arrests (1.0) that is considerably higher than the other groups. Among active arrestees (those with at least one arrest), however, the disparity in the mean number of arrests between blacks (3.4) and the other groups is considerably smaller. One may conclude from this that it is the far greater prevalence of arrest among blacks that accounts for the racial disproportionality of arrest than any greater frequency or incidence of arrest among active offenders.

Table 2 displays summary statistics by racial and ethnic groups for the relevant predictors in the study, demonstrating that visible differences exist across groups on key individual-, family-, and neighborhood-level characteristics. Here it can be seen that all Latinos are more likely first- or second-generation immigrants than third-or-higher-generation immigrants. In contrast, almost all black youths and three-quarters of white youths are third-generation immigrants or higher. In terms of family characteristics, socioeconomic status is highest among whites and lowest among Mexicans. However, Mexicans more commonly have married parents than other groups, and black youths are more likely to have adult extended family members living in the same household. Family control is greatest in black families and lowest in Mexican families. Blacks have a greater propensity for self-reported criminal offending than other groups, and Mexicans have the lowest levels of self-reported criminal offending.

Regarding neighborhood characteristics, blacks, on average, live in areas characterized by higher levels of concentrated poverty than other groups, whereas whites live in areas with the lowest levels of concentrated poverty. Blacks also live in neighborhoods with relatively high levels of residential stability and low percentages of foreign-born residents. On average, whites live in neighborhoods with a higher tolerance of deviance than other groups, which is a finding consistent with the work of Sampson and Bartusch (1998). Still, whites also tend to live in neighborhoods with high levels of collective efficacy. Latinos live in neighborhoods with the lowest levels of collective efficacy.

**Table 2. Descriptive Statistics (means, with standard deviations in parentheses) by Race/Ethnicity: PHDCN Cohorts 12–18 ($N$ = 1,775)**

| Variables | Black ($N$ = 641) | Mexican ($N$ = 560) | Other Latino ($N$ = 227) | Other Race ($N$ = 68) | White ($N$ = 279) |
|---|---|---|---|---|---|
| Individual- and Family-Level Variables | | | | | |
| Male | 0.47 (0.50) | 0.50 (0.50) | 0.49 (0.50) | 0.62 (0.49) | 0.51 (0.50) |
| Age at Wave 1 | 14.80 (2.52) | 14.67 (2.40) | 14.63 (2.35) | 15.08 (2.53) | 15.03 (2.46) |
| Cohort proportions | | | | | |
| Cohort 12 | 0.40 (0.49) | 0.42 (0.49) | 0.40 (0.49) | 0.35 (0.48) | 0.36 (0.48) |
| Cohort 15 | 0.31 (0.46) | 0.33 (0.47) | 0.37 (0.48) | 0.31 (0.47) | 0.33 (0.47) |
| Cohort 18 | 0.29 (0.45) | 0.25 (0.44) | 0.24 (0.43) | 0.34 (0.48) | 0.31 (0.46) |
| Immigrant generation | | | | | |
| First | 0.02 (0.14) | 0.31 (0.46) | 0.24 (0.43) | 0.22 (0.42) | 0.13 (0.40) |
| Second | 0.02 (0.15) | 0.55 (0.50) | 0.54 (0.50) | 0.35 (0.48) | 0.11 (0.32) |
| Third or higher | 0.96 (0.20) | 0.15 (0.35) | 0.22 (0.42) | 0.43 (0.50) | 0.75 (0.43) |
| Family socioeconomic status | 0.23 (1.26) | –0.66 (1.05) | –0.24 (1.22) | 0.21 (1.13) | 0.84 (1.37) |
| Married parents | 0.30 (0.46) | 0.72 (0.45) | 0.43 (0.50) | 0.68 (0.47) | 0.64 (0.48) |
| Adult extended family | 0.27 (0.45) | 0.14 (0.34) | 0.14 (0.34) | 0.21 (0.41) | 0.11 (0.31) |
| Number of children | 3.31 (1.96) | 3.88 (1.75) | 3.17 (1.35) | 3.18 (1.82) | 2.74 (1.51) |
| Family control | 60.87 (7.41) | 55.91 (9.39) | 57.93 (8.02) | 57.26 (9.14) | 57.32 (9.42) |
| Self-reported criminal offending | 0.29 (0.81) | –0.08 (0.70) | 0.13 (0.80) | 0.18 (0.91) | 0.11 (0.81) |
| Neighborhood-Level Variables | | | | | |
| % black | 77.99 (26.05) | 12.81 (20.40) | 11.75 (18.61) | 0.25 (0.33) | 9.15 (18.37) |
| % Mexican | 11.19 (16.39) | 57.63 (26.76) | 39.97 (19.87) | 0.20 (0.16) | 21.96 (17.35) |
| % other Latino | 4.16 (8.61) | 16.20 (14.52) | 29.92 (13.98) | 0.11 (0.13) | 12.31 (12.94) |
| % other race | 2.68 (3.91) | 2.42 (4.28) | 3.23 (5.81) | 0.12 (0.07) | 7.83 (7.00) |
| % white | 3.98 (9.20) | 10.94 (16.63 | 15.13 (16.82) | 0.32 (0.29) | 48.75 (24.75) |

*(continued)*

*(Table 2, continued)*

| Variables | Black ($N$ = 641) | Mexican ($N$ = 560) | Other Latino ($N$ = 227) | Other Race ($N$ = 68) | White ($N$ = 279) |
|---|---|---|---|---|---|
| Neighborhood-Level Variables (cont.) | | | | | |
| Concentrated poverty | 0.33 | –0.25 | –0.27 | –0.48 | –0.70 |
| | (0.79) | (0.43) | (0.58) | (0.67) | (0.48) |
| % foreign-born | 9.51 | 30.20 | 27.19 | 23.15 | 21.20 |
| | (12.06) | (12.23) | (10.97) | (13.90) | (13.08) |
| Residential stability | 0.35 | –0.25 | –0.30 | –0.15 | 0.07 |
| | (1.19) | (0.67) | (0.61) | (1.04) | (0.96) |
| Tolerance of deviance | 0.78 | 0.74 | 0.73 | 0.81 | 0.80 |
| | (0.11) | (0.13) | (0.12) | (0.12) | (0.11) |
| Collective efficacy | 3.87 | 3.84 | 3.84 | 4.00 | 4.08 |
| | (0.23) | (0.23) | (0.23) | (0.28) | (0.29) |

## Growth Curve Analyses of Arrest

Table 3 displays results from the estimation of Eq. (2), where Model 1 is the baseline model. Results from Model 1 reveal substantial differences in the expected number of arrests at age 17 (i.e., the intercept) across race and ethnicity. The expected count of arrests for black males is 0.45; for Mexican males is 0.16; for other Latino males is 0.16; and for white males is 0.14.[4] A sizable gender difference in arrest can also be seen. Additionally, I find significant cohort differences in arrest, such that members of the 15-year-old and 18-year-old cohorts are less likely to be arrested at age 17 than those of the 12-year-old cohort.

To illustrate the disparities in arrest across race and ethnicity, Figure 2 displays the expected age-arrest curves for males aged 10–25, constructed from model coefficients from Model 1. Here it can be seen that the level or number of arrests is substantially greater for black males. The curves for Mexican, other Latino, and white males overlap for the most part, with the curve for white males slightly lower than the two curves for Latino males.

Model 2 of Table 3 includes neighborhood-level indicators of the percentage of each racial and ethnic group in a given neighborhood. Adding both the percentage of racial and ethnic composition at the neighborhood level and the dummy indicators at the person level makes it possible to distinguish between person-level and contextual effects. A contextual effect refers to some emergent property of a neighborhood that is associated with arrest, even after the demographic composition of neighborhoods is controlled for. When both the person-level dummy variables and their neighborhood aggregates are grand mean–centered, the coefficients for the race and ethnicity dummy variables are interpreted as the disparity in arrest between black youths and youths of other racial and ethnic groups who reside in the same neighborhood (see Raudenbush and Bryk 2002:139–41). The coefficients for the neighborhood-level racial and ethnic composition variables are interpreted as the arrest disparity between two youths of the same given race and ethnicity who reside in different

4. Because the Level 2 predictors are grand-mean centered, the expected count for black males is predicted as follows:

$$E\left(Y_t^{Black}\right) = \exp\left(\beta_0 + \beta_{White}(0 - \bar{X}_{White}) + \beta_{Mex}(0 - \bar{X}_{Mex}) + \beta_{OthLat}(0 - \bar{X}_{OthLat})\right.$$
$$\left. + \beta_{OthRace}(0 - \bar{X}_{OthRace}) + \beta_{Male}(1 - \bar{X}_{Male}).\right.$$

The expected count at age 17 is predicted in a similar fashion for other racial and ethnic groups.

**Table 3. Racial/Ethnic Disparities in Arrest, With Individual and Neighborhood Characteristics**

| | Model 1 | | Model 2 | | Model 3 | |
|---|---|---|---|---|---|---|
| Variables | Coefficient | *SE* | Coefficient | *SE* | Coefficient | *SE* |
| Intercept (expected count of arrests at age 17) | –2.408*** | 0.067 | –2.418*** | 0.068 | –2.389*** | 0.070 |
| Neighborhood-Level Variables | | | | | | |
| % white | | | 0.041 | 0.048 | | |
| % Mexican | | | –0.060 | 0.031 | | |
| % other Latino | | | 0.118* | 0.054 | | |
| % other race | | | 0.073 | 0.102 | | |
| Concentrated poverty | | | | | 0.190* | 0.075 |
| % foreign-born | | | | | –0.007 | 0.008 |
| Residential stability | | | | | –0.185* | 0.078 |
| Individual-Level Variables | | | | | | |
| Race/Ethnicity (vs. black) | | | | | | |
| White | –1.151*** | 0.156 | –1.370*** | 0.265 | –0.913*** | 0.163 |
| Mexican | –1.074*** | 0.169 | –1.011*** | 0.238 | –0.936*** | 0.248 |
| Other Latino | –1.032*** | 0.118 | –1.181*** | 0.181 | –0.916*** | 0.133 |
| Other race | –1.414*** | 0.280 | –1.579*** | 0.317 | –1.238*** | 0.273 |
| Male | 1.842*** | 0.120 | 1.844*** | 0.117 | 1.837*** | 0.120 |
| Cohort (vs. cohort 12) | | | | | | |
| Cohort 15 | –0.705*** | 0.123 | –0.701*** | 0.122 | –0.667*** | 0.123 |
| Cohort 18 | –0.903*** | 0.139 | –0.913*** | 0.139 | –0.843*** | 0.140 |
| Age | 0.455*** | 0.024 | 0.453*** | 0.024 | 0.456*** | 0.024 |
| $Age^2$ | –0.087*** | 0.005 | –0.086*** | 0.005 | –0.087*** | 0.005 |

*Notes:* Coefficients and standard errors for the neighborhood composition indicators have been divided by 10. Age is centered at 17.

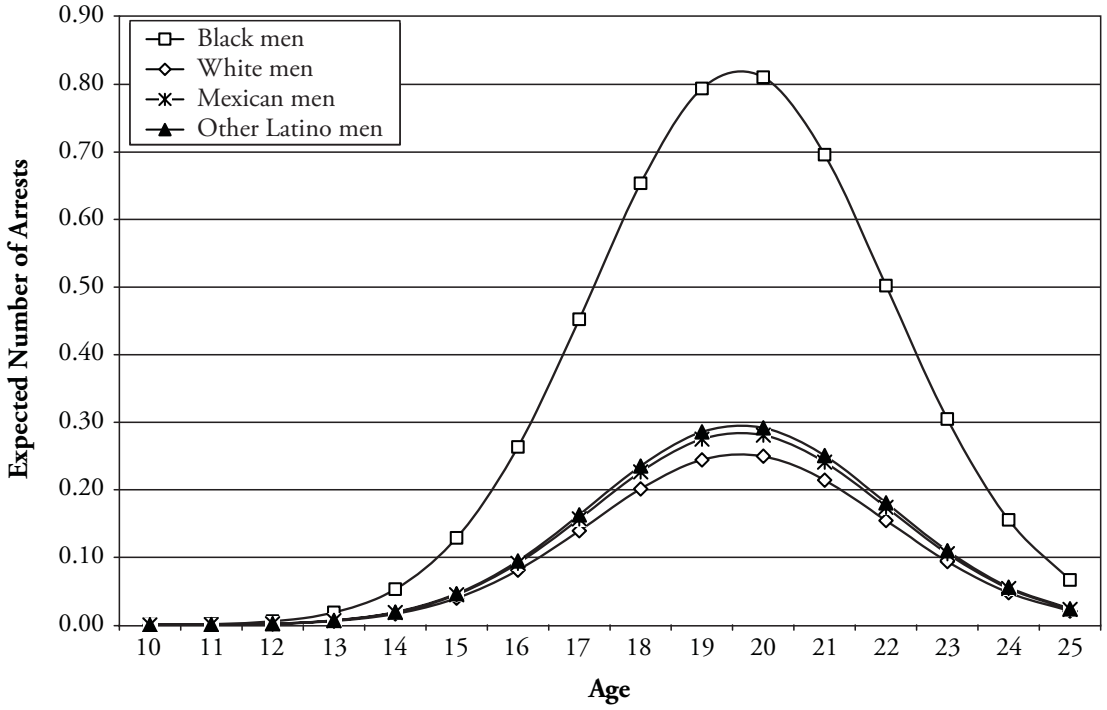
*$p \leq .05$; ***$p \leq .001$

neighborhoods that have a one-unit difference in racial and ethnic composition. In the present case, the unit is a 10% difference in composition.

Results from Model 2 of Table 3 reveal that white youths residing in the same neighborhood as black youths have an expected count of arrests that is 74.6% lower than black youth ($100 \times [\exp(\gamma_{White}) - 1] = 100 \times [\exp(-1.370) - 1] = -74.6$). Similarly, Mexican youths have an expected count of arrests that is 63.6% lower than black youth; for other Latino youths, the difference is 69.3%. As for the contextual effects, a 10% increase in the white composition of a neighborhood above the sample average equates to a 4.2% increase in the expected count of arrests at age 17 for an average youth ($100 \times [\exp(\gamma_{White}) - 1] = 100 \times [\exp(0.041) - 1] = 4.2$). A 10% increase in the Mexican composition of a neighborhood above the sample average equates to a 5.8% decrease in the expected count of arrests at age 17. Finally, a 10% increase in the other Latino composition of a neighborhood above the sample average equates to a 12.5% increase in the expected count of arrests at age 17. Only the other Latino neighborhood composition indicator is significantly associated with arrest.

Overall, these results suggest that much of the disparity in arrest is between members of various racial and ethnic groups within respective neighborhoods, and less so between

**Figure 2. Age-Arrest Curves for Men, by Race/Ethnicity: PHDCN Cohorts 12–18**




like individuals in different neighborhoods. However, research generally supports the notion that neighborhoods are more internally heterogeneous than externally differentiable, such that more within-neighborhood variability in arrest should be expected than between-neighborhood variability (Cook, Shagle, and Degirmencioglu 1997). Thus, the next series of models adds predictors of neighborhood structure and social and cultural processes to determine which factors influence the likelihood of arrest.

Model 3 in Table 3 includes neighborhood-level measures of concentrated poverty, the percentage of foreign-born residents, and residential stability. Given the lack of association between the indicators of neighborhood racial and ethnic composition and arrest (besides the "other Latino" measure), I remove these measures from the model. Findings from Model 3 reveal that concentrated poverty is positively associated with arrest, and residential stability is negatively associated with arrest. With the addition of these three predictors in Model 3, the gap in arrest between black youths and white youths decreases from –1.151 in Model 1 to –0.913, which is a 20.7% decline. Likewise, with the addition of neighborhood predictors, gaps between black youths and the various Latino groupings shrink considerably.

Results to this point suggest that certain neighborhood conditions—concentrated poverty and residential stability in particular—are associated with arrest. As a means of examining whether neighborhood social and cultural processes explain disparities in arrest, Model 4 in Table 4 adds measures of collective efficacy and tolerance of deviance. Results show that the inclusion of these covariates actually strengthens the association between concentrated poverty and arrest. However, neither collective efficacy nor tolerance of deviance is significantly related to the age-17 arrest count. Moreover, gaps in arrest between

**Table 4. Racial/Ethnic Disparities in Arrest, With Individual, Family, and Neighborhood Characteristics**

| | Model 4 | | Model 5 | | Model 6 | | Model 7 | |
|---|---|---|---|---|---|---|---|---|
| Variables | Coefficient | *SE* | Coefficient | *SE* | Coefficient | *SE* | Coefficient | *SE* |
| Intercept (expected count of arrests at age 17) | –2.392*** | 0.070 | –2.502*** | 0.069 | –2.609*** | 0.068 | –2.623*** | 0.070 |
| Neighborhood-Level Variables | | | | | | | | |
| Concentrated poverty | 0.309** | 0.096 | 0.207* | 0.094 | 0.214* | 0.093 | 0.232* | 0.100 |
| % foreign-born | 0.000 | 0.007 | 0.006 | 0.007 | 0.008 | 0.006 | 0.009 | 0.006 |
| Residential stability | –0.160 | 0.094 | –0.093 | 0.091 | –0.088 | 0.097 | –0.043 | 0.106 |
| Collective efficacy | 0.477 | 0.483 | 0.351 | 0.423 | 0.360 | 0.478 | 0.334 | 0.558 |
| Tolerance of deviance | 0.644 | 0.481 | 0.728 | 0.503 | 0.977 | 0.507 | 1.235* | 0.540 |
| Individual-Level Variables | | | | | | | | |
| Race/Ethnicity (vs. black) | | | | | | | | |
| White | –0.952*** | 0.176 | –0.651*** | 0.196 | –0.632** | 0.199 | –0.587** | 0.207 |
| Mexican | –0.955*** | 0.221 | –0.425 | 0.246 | –0.488* | 0.240 | –0.503* | 0.252 |
| Other Latino | –0.914*** | 0.124 | –0.451** | 0.158 | –0.561*** | 0.156 | –0.567*** | 0.166 |
| Other race | –1.278*** | 0.291 | –0.900*** | 0.268 | –1.106*** | 0.222 | –1.159*** | 0.217 |
| Male | 1.825*** | 0.121 | 1.843*** | 0.119 | 1.731*** | 0.118 | 1.735*** | 0.120 |
| Cohort (vs. cohort 12) | | | | | | | | |
| Cohort 15 | –0.656*** | 0.123 | –0.695*** | 0.132 | –1.019*** | 0.132 | –1.017*** | 0.135 |
| Cohort 18 | –0.843*** | 0.143 | –0.840*** | 0.161 | –1.124*** | 0.155 | –1.141*** | 0.156 |
| Age | 0.457*** | 0.024 | 0.457*** | 0.024 | 0.458*** | 0.023 | 0.458*** | 0.023 |
| $Age^2$ | –0.087*** | 0.005 | –0.087*** | 0.005 | –0.087*** | 0.005 | –0.087*** | 0.005 |
| Immigrant generation (vs. third or higher) | | | | | | | | |
| First generation | | | –0.667** | 0.231 | –0.349 | 0.248 | –0.338 | 0.253 |
| Second generation | | | –0.646*** | 0.195 | –0.557** | 0.187 | –0.548** | 0.191 |
| Family socioeconomic status | | | –0.081 | 0.049 | –0.110* | 0.052 | –0.125* | 0.054 |
| Married parents | | | –0.718*** | 0.112 | –0.693*** | 0.116 | –0.688*** | 0.114 |
| Adult extended family | | | 0.152 | 0.121 | 0.207 | 0.131 | 0.251 | 0.132 |
| Number of children | | | 0.048* | 0.023 | 0.040 | 0.024 | 0.040 | 0.025 |
| Family control | | | 0.000 | 0.006 | 0.002 | 0.006 | 0.004 | 0.006 |
| Self-reported criminal offending (SRO) | | | | | 0.564*** | 0.060 | 0.598*** | 0.061 |
| SRO × Concentrated poverty | | | | | | | –0.105 | 0.110 |
| SRO × % foreign-born | | | | | | | –0.005 | 0.006 |
| SRO × Residential stability | | | | | | | –0.214* | 0.085 |
| SRO × Collective efficacy | | | | | | | 0.221 | 0.467 |
| SRO × Tolerance of deviance | | | | | | | –1.373*** | 0.412 |

*Note:* Age is centered at 17.

*$p \leq .05$; **$p \leq .01$; ***$p \leq .001$

black youths and other groups remain essentially the same after I adjust for these two additional neighborhood predictors.

Model 5 of Table 4 includes family-level factors with the individual demographic and neighborhood-level predictors. Results from this model reveal that the expected number of arrests is significantly lower for more-recent immigrants (first or second generation). Results also show that family socioeconomic status is marginally related to arrest ($p = .099$) as well as a significant difference in arrest, on average, between individuals with married parents and those without married parents. Although having extended family members in the household is unrelated to arrest, arrest is more likely for youths in households with greater numbers of children. Surprisingly, the indicator of family control is unrelated to arrest.

In terms of the influence of family-level covariates on disparities in arrest, the addition of family variables reduces the coefficient for the black-white gap in arrest at age 17 from –0.952 to –0.651, a decline of 31.6%. However, the remaining difference between black youth and white youth is still substantial and statistically significant. With the black-Mexican arrest gap, the coefficient is reduced by 55.5% and the gap is no longer statistically significant. In sum, numerous family-level covariates are significantly and substantially associated with arrest, and racial and ethnic differences in family demographics and structure explain large percentages of the disparities in arrest between black youths and youths from other racial and ethnic groups.

At this point, it is important to ask whether the inclusion of family-level covariates weakens the association between neighborhood predictors and arrest. Comparing neighborhood coefficients in Models 4 and 5 reveals that the inclusion of family-level covariates in Model 5 attenuates the association between concentrated poverty and arrest, reducing the size of the coefficient by 33%. The coefficient for tolerance of deviance has increased from 0.644 to 0.728 with the inclusion of family-level correlates of arrest, although the association is not significant.

Model 6 enters a scale of self-reported criminal offending to determine the extent to which residual racial and ethnic differences in arrest are explained by group differences in criminal offending. As shown in Table 4, the measure of criminal offending is highly associated with arrest, which is expected. However, inclusion of the offending measure does not lead to much or any further reduction in the arrest gap between black youths and other youths. This finding contrasts previous research that concluded that differential involvement in crime across groups explains a substantial portion of racial differences in arrest and criminal case processing (Blumstein 1982; Hindelang 1978). Part of the reason for such modest reductions in the arrest gap between blacks and other groups is that analyses already include a number of covariates that are highly associated with arrest and that differ greatly across race and ethnicity (e.g., family structure). That said, the decomposition analysis to follow clarifies to what extent differences in offending explain the gaps in arrest across groups.

Findings from Model 6 also reveal that the addition of offending to the model does little to mediate the effect of neighborhood structure on arrest. This finding suggests that the higher level of criminal offending in certain neighborhoods (e.g., neighborhoods characterized by concentrated poverty) does not explain why the probability of arrest is higher in those neighborhoods. Perhaps the most interesting finding is that the addition of offending to the model substantially strengthens the association between arrest and tolerance of deviance to the point where tolerance is now marginally related to arrest ($p = .057$).

To explore the relation between arrest, offending, and tolerance of deviance in greater detail, Model 7 (Table 4) examines whether neighborhood conditions affect the association between criminal offending and arrest. I am particularly interested in whether offending is any more or less likely to lead to arrest in neighborhoods characterized by tolerant attitudes toward deviance. In Model 7, the positive main effect of tolerance of deviance on arrest implies that arrest is more frequent in neighborhoods with greater tolerance of deviance.

Focusing on the interaction between offending and tolerance of deviance, results show a significant, negative interaction between these two measures, which can be interpreted to mean that the association between criminal offending and arrest is weaker in neighborhoods with higher tolerance of deviance. Put differently, the likelihood of getting arrested following the commission of a crime is lower in neighborhoods with a high tolerance of deviance. One potential reason why this occurs is that residents are less likely to report crimes to police in high-tolerance neighborhoods.

## Decomposition of Racial and Ethnic Differences in Arrest

Results suggest that a number of factors explain racial and ethnic differences in arrest. As the next step, analyses focus on explaining the gaps in arrest between groups by decomposing the difference in arrest into differences in specific attributes and differences in coefficients. Table 5 presents the group-specific regression coefficients which, along with group-specific mean attributes, are used to decompose the arrest gap between black youths and white youths, as well between black and Mexican youths.

As shown in Table 5, the size and direction of several coefficients differ across groups. For instance, family socioeconomic status is a significant, negative correlate of arrest for blacks and whites, but not for Mexicans. For black youths, results show a significant, negative interaction of self-reported offending and tolerance of deviance with arrest. As with Model 7 in Table 4, this finding can be interpreted to mean that the association between criminal offending and arrest of black youths is weaker in neighborhoods with higher tolerance of deviance. However, this association does not hold in the Mexican and white models. Interestingly, the white model shows a significant, positive association between collective efficacy and arrest. Thus, the probability of white arrest given offending is higher in neighborhoods with relatively greater levels of collective efficacy. Still, the negative interaction of offending and collective efficacy with arrest implies that the association between criminal offending and arrest is weaker in neighborhoods with higher levels of collective efficacy.

Figure 3 displays the results of the decomposition of black-white and black-Mexican differences in arrest at age 17. Here, the gap is roughly the same size for whites and Mexicans, with a difference of 0.12 arrests. About 0.05 of the 0.12 arrest gap would be eliminated if black subjects had similar attributes (i.e., individual, family, and neighborhood characteristics) as white subjects. The remaining gap of approximately 0.07 arrests of 0.12 is explained by differences in coefficients, both intercepts and slopes. For the black-Mexican arrest gap, only about 0.02 of the 0.12 gap would be eliminated if black subjects had similar attributes as Mexican subjects.

Figure 4 displays the percentage reduction in the gap in arrest at age 17 between blacks and the other racial and ethnic groups that results when substituting the mean values of attributes from the other groups. The first set of columns in Figure 4 illustrates that 11% of this gap would hypothetically be reduced if blacks lived in neighborhoods with similar levels of poverty as whites (–0.70 instead of 0.33, as shown in Table 2). This procedure, in effect, equalizes neighborhood poverty across groups and reveals how much of the arrest disparity occurs because blacks and whites live in distinct neighborhood contexts, on average.

In Figure 4, the first bar in each set represents the black-white arrest disparity at age 17, and the second bar represents the black-Mexican disparity. For the black-white disparity, the greatest reduction in the arrest gap comes from equalizing aspects of family structure (married parents; and to a lesser extent, family socioeconomic status). Furthermore, equalizing levels of criminal offending also reduces the arrest gap by a considerable amount. Given that tolerance of deviance is actually lower in neighborhoods where black subjects reside relative to white subjects (see Table 2), equalizing levels of tolerance of deviance leads to a very slight increase in the black-white arrest gap (a negative reduction in the gap).

**Table 5. Group-Specific Models for Nonlinear Decomposition of Group Differences in Arrest**

| | Black | | Mexican | | White | |
|---|---|---|---|---|---|---|
| Variables | Coefficient | *SE* | Coefficient | *SE* | Coefficient | *SE* |
| Intercept (expected count of arrests at age 17) | –1.857*** | 0.065 | –3.338*** | 0.150 | –3.395*** | 0.266 |
| Neighborhood-Level Variables | | | | | | |
| Concentrated poverty | 0.152* | 0.074 | 0.610 | 0.306 | 1.085* | 0.526 |
| % foreign-born | 0.020*** | 0.005 | –0.017 | 0.015 | 0.124*** | 0.027 |
| Residential stability | 0.050 | 0.103 | –0.458** | 0.166 | –0.742 | 0.521 |
| Collective efficacy | 0.172 | 0.512 | 0.824 | 0.870 | 5.895*** | 1.029 |
| Tolerance of deviance | 0.893 | 0.602 | 0.601 | 1.301 | 5.107 | 3.043 |
| Individual-Level Variables | | | | | | |
| Male | 1.674*** | 0.143 | 2.267*** | 0.201 | 1.218* | 0.571 |
| Cohort (vs. cohort 12) | | | | | | |
| Cohort 15 | –0.922*** | 0.196 | –1.180*** | 0.286 | –1.550** | 0.517 |
| Cohort 18 | –1.121*** | 0.196 | –1.490*** | 0.382 | –1.977*** | 0.588 |
| Age | 0.457*** | 0.025 | 0.400*** | 0.047 | 0.580*** | 0.047 |
| $Age^2$ | –0.081*** | 0.006 | –0.072*** | 0.011 | –0.127*** | 0.011 |
| Family socioeconomic status | –0.136* | 0.055 | 0.104 | 0.102 | –0.341* | 0.158 |
| Married parents | –0.485** | 0.161 | –0.838*** | 0.252 | –1.772*** | 0.529 |
| Adult extended family | 0.403** | 0.155 | –0.249 | 0.552 | –0.418 | 0.785 |
| Number of children | 0.086*** | 0.024 | 0.049 | 0.063 | –0.084 | 0.127 |
| Family control | 0.001 | 0.008 | 0.028** | 0.009 | –0.022 | 0.031 |
| Self-reported criminal offending (SRO) | 0.476*** | 0.089 | 0.751*** | 0.140 | 0.483 | 0.300 |
| SRO × Concentrated poverty | –0.097 | 0.127 | 0.068 | 0.257 | –0.491 | 0.521 |
| SRO × % foreign-born | 0.002 | 0.008 | –0.027* | 0.011 | –0.017 | 0.035 |
| SRO × Residential stability | –0.200 | 0.110 | –0.417* | 0.212 | 1.085*** | 0.303 |
| SRO × Collective efficacy | 0.407 | 0.551 | 0.932* | 0.450 | –2.875* | 1.246 |
| SRO × Tolerance of deviance | –2.971*** | 0.630 | –1.493 | 0.803 | 0.364 | 1.929 |

*Notes:* Age is centered at 17. Because of lack of variation in immigrant generational status for black subjects (i.e., 96% of subjects are third-generation immigrants or higher), measures of immigrant status have been dropped from decomposition analyses.

*$p \leq .05$; **$p \leq .01$; ***$p \leq .001$

For the black-Mexican arrest disparity, equalizing levels of poverty, parental marital status, and offending all result in a 9% to 25% reduction in the arrest gap. Given that, on average, family socioeconomic status is lower for Mexican youths relative to black youths, equalizing levels of socioeconomic status leads to an increase in the black-Mexican arrest gap. Equalizing levels of neighborhood tolerance of deviance leads to a 5% reduction in the black-Mexican arrest gap. Overall, these results suggest that neighborhood and familial context explain some of the group differences in arrest. Yet, even if blacks were situated

**Figure 3. Decomposition of Group Differences in Arrest at Age 17**

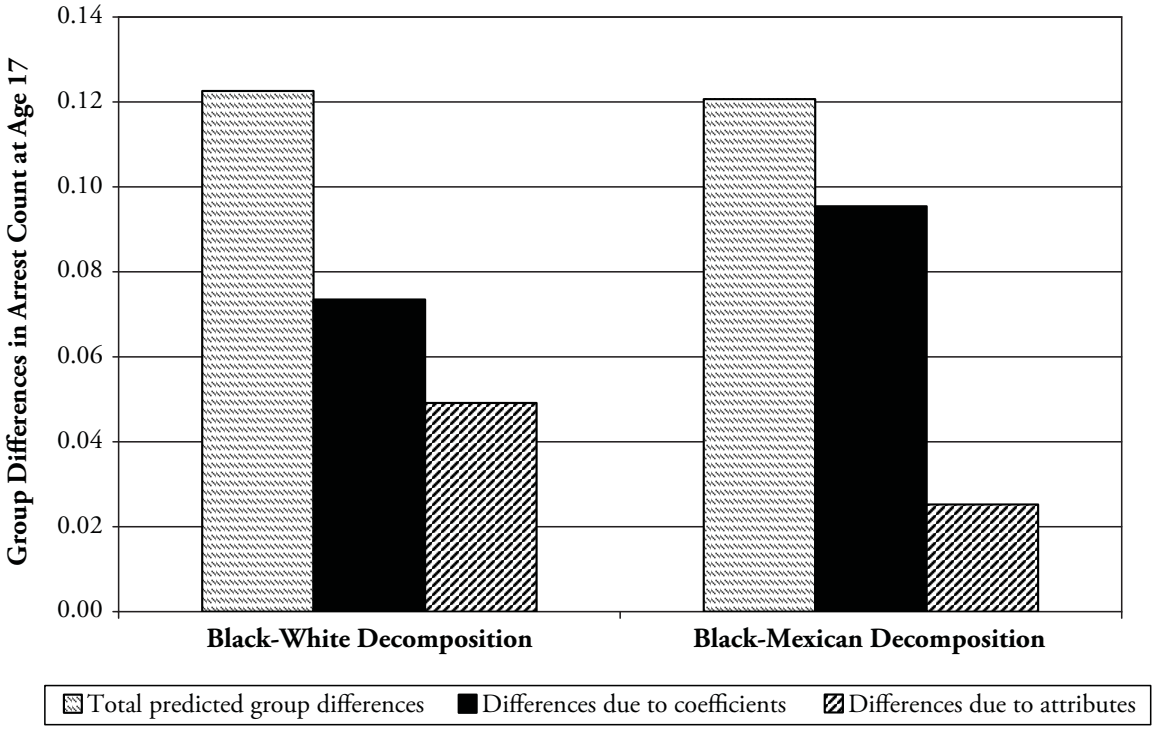



**Figure 4. Percentage of Racial and Ethnic Arrest Differences at Age 17 Explained by Neighborhood, Family, and Offending Differences**

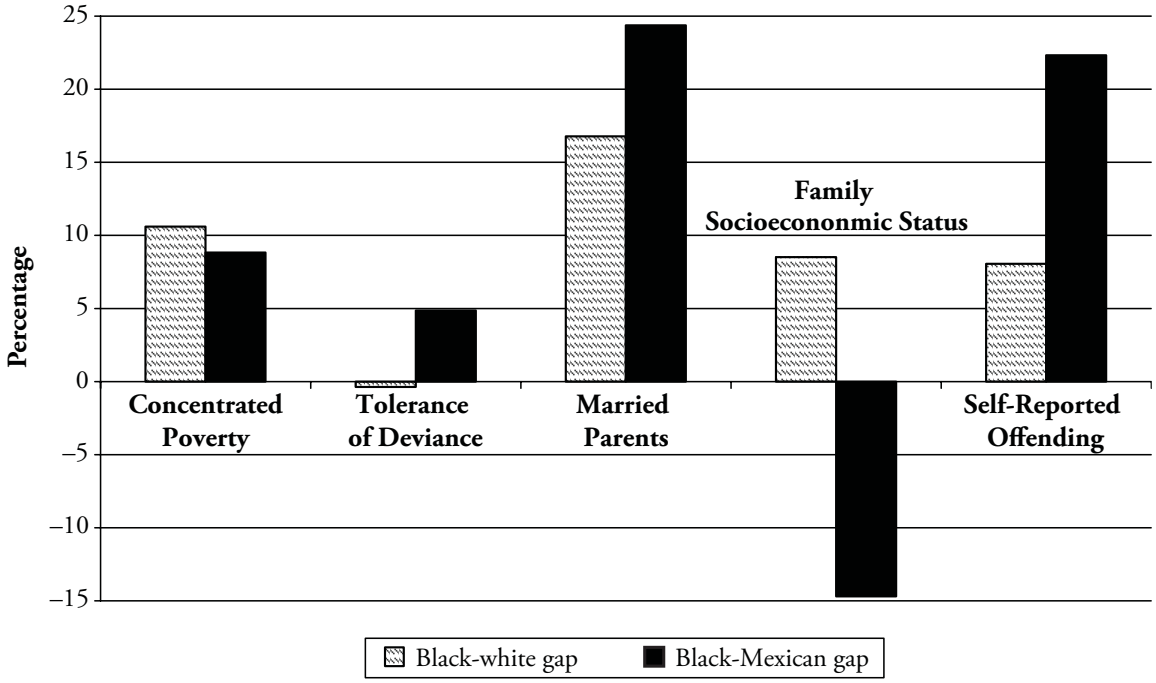
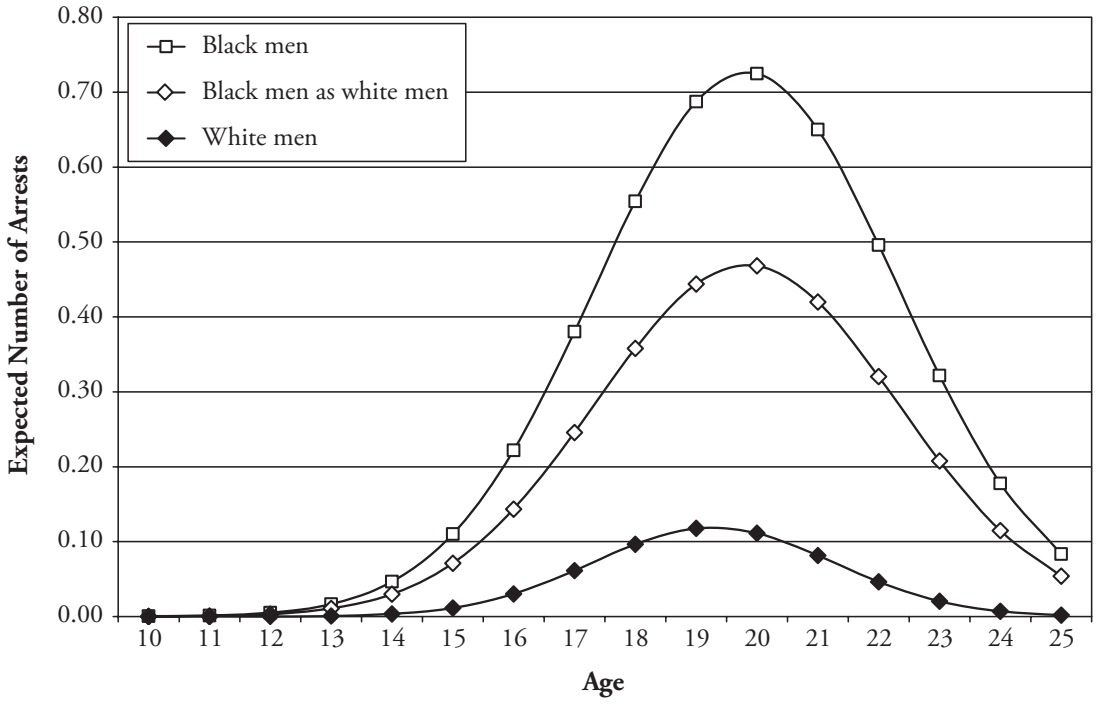


**Figure 5. Age-Arrest Curves for Black Versus White Males Accounting for Group Differences in Individual, Family, and Neighborhood Characteristics**




in social contexts similar to other racial and ethnic groups, they would still exhibit greater incidence of arrest.

To conclude the decomposition analysis, Figure 5 displays age-arrest curves for black males and white males, and the hypothetical black curve if black subjects had the same level of attributes as white youths. This figure illustrates that a substantial proportion of the gap in arrest at age 17 is reduced by equalizing attributes (from 0.32 to 0.18, or 44%). However, a sizable unexplained area between the white male curve and the black-as-white male curve still exists, which is reflected by differences in intercepts and slope coefficients across groups.

## DISCUSSION

The primary objective of this study is to examine the extent to which social context explains racial and ethnic disparities in arrest. Given that youths from different racial and ethnic groups grow up, on average, in distinct social contexts, it is critical to move beyond individual-level explanations for racial and ethnic disparities in arrest, and instead broaden the focus to include contextual factors.

In regard to the first hypothesis advanced at the outset of this paper, findings reveal that select structural features of neighborhoods are associated with arrest. With respect to the combined models presented in Tables 3 and 4, results show that concentrated poverty is positively related to arrest and explains a large portion of group differences in arrest, particularly black-white differences.

Related to the second hypothesis, results show that collective efficacy is unrelated to arrest. Tolerance of deviance is positively related to arrest, such that arrest is more likely

in neighborhoods characterized by high levels of tolerance. However, after consideration of the interaction between neighborhood tolerance of deviance and criminal offending, results show that the probability of getting arrested *following the commission of a crime* is lower in high-tolerance neighborhoods. In sum, it appears that neighborhood tolerance of deviance influences the amount of crime in a given neighborhood and whether crimes ultimately end in an arrest.

Regarding the third hypothesis and the influence of family factors on arrest, results reveal that immigrant generational status, parental marital status, and socioeconomic status are all significantly associated with arrest; family control, the presence of extended family members, and the number of household children are unrelated to arrest. Furthermore, family structural characteristics explain sizable portions of group differences in arrest, attenuating the association between concentrated poverty and arrest.

Through a decomposition analysis, I partition the group differences in arrest into differences in coefficients and differences in attributes, and then further decompose the attribute differences to isolate the influence of particular covariates. Findings presented in Figures 3–5 reveal that equalizing attributes across groups substantially narrows the arrest gap between groups. Yet, even after accounting for relevant individual-, family-, and neighborhood-level predictors, substantial residual arrest differences remain between black youths and youths of other racial and ethnic groups.

Two limitations of the study should be noted. First is the threat to internal validity due to the possibility of selection bias. Selection bias may come in many forms, although in a study of neighborhood effects, the assignment of individuals to neighborhoods is of particular importance. Individuals are often constrained in decisions of where to live, but they do have at least a minor influence on those decisions. Selection bias may occur when an unobserved characteristic of individuals or families influences both where they live and the outcome under study, and may therefore account for any relation between neighborhood characteristics and outcomes. Besides omitted variables related to neighborhood assignment, internal validity may also be questioned because of other omitted variables and untested relationships. As I note in the earlier Conceptual Framework section, my focus in this manuscript is on the direct effects of neighborhood characteristics on arrest. However, various family factors may mediate or moderate the influence of neighborhoods on youths' behavior. The omission of these intervening relationships from analyses is another threat to internal validity, which should be addressed in future analyses. Likewise, measures of police behavior and the situational factors associated with the decision to arrest (i.e., the demeanor of the suspect, the victim-offender relationship, and the seriousness of the offense) should also be examined in future analyses.

As a second limitation, this analysis used a subset of youths from the full PHDCN sample who consented to have their official criminal records searched. This subsample showed no significant difference in the average number of self-reported arrests compared with youth subjects who did not consent to a criminal records search. However, Table A1 in the Appendix does show that these subsamples differ on certain observed characteristics. To the extent that this subsample is statistically different from the rest of the sample, it may be that the analytic sample is no longer a representative sample of Chicago youth.

Clearly, more research should be done to disentangle the factors that ultimately produce demographic disparities in arrest. Findings thus far suggest that black youths face multiple layers of disadvantage that ultimately make it more likely for these youths to be arrested than youths from other racial and ethnic groups. Disadvantage comes in the form of unstable family structures and deleterious neighborhood conditions, with residual arrest differences still left to be explained.

**Appendix Table A1. Comparison of Subsamples, PHDCN Cohorts 12–18**

| | Subsample: Consented to Records Search ($N$ = 1,775) | | Subsample: Did Not Consent to Records Search ($N$ = 375) | | Comparison | |
|---|---|---|---|---|---|---|
| Variable | Mean | *SD* | Mean | *SD* | Test Statistic | *p* Value |
| Male | 0.49 | 0.50 | 0.51 | 0.50 | 0.392 | .531 |
| Age at Wave 1 | 14.78 | 2.45 | 15.40 | 2.51 | 19.117 | < .001 |
| Cohort Proportions | | | | | | |
| Cohort 12 | 0.40 | 0.49 | 0.31 | 0.46 | 10.113 | .001 |
| Cohort 15 | 0.33 | 0.47 | 0.31 | 0.46 | 0.227 | .634 |
| Cohort 18 | 0.28 | 0.45 | 0.38 | 0.49 | 15.025 | < .001 |
| Race and Ethnicity | | | | | | |
| Black | 0.36 | 0.48 | 0.44 | 0.50 | 7.035 | .007 |
| Mexican | 0.32 | 0.46 | 0.23 | 0.42 | 11.033 | .001 |
| Other Latino | 0.13 | 0.33 | 0.14 | 0.35 | 0.424 | .236 |
| White | 0.16 | 0.36 | 0.15 | 0.35 | 0.313 | .576 |
| Other race | 0.04 | 0.19 | 0.05 | 0.21 | 0.554 | .456 |
| Immigrant Generation | | | | | | |
| First | 0.16 | 0.37 | 0.18 | 0.39 | 0.836 | .360 |
| Second | 0.28 | 0.45 | 0.21 | 0.41 | 7.450 | .006 |
| Third or higher | 0.56 | 0.50 | 0.61 | 0.49 | 3.076 | .079 |
| Family | | | | | | |
| Family socioeconomic status | –0.01 | 1.32 | –0.07 | 1.19 | 0.496 | .482 |
| Married parents | 0.52 | 0.50 | 0.42 | 0.49 | 12.005 | .001 |
| Adult extended family | 0.18 | 0.39 | 0.16 | 0.37 | 1.097 | .295 |
| Number of children | 3.37 | 1.79 | 3.37 | 1.81 | 0.001 | .980 |
| Family control | 58.22 | 8.79 | 58.45 | 9.42 | 0.185 | .667 |
| Self-Reported Criminal Offending | 0.12 | 0.79 | 0.24 | 0.88 | 6.365 | .012 |
| Self-Reported Arrest, Wave 1 | 0.17 | 0.89 | 0.22 | 0.87 | 1.027 | .311 |
| Self-Reported Arrest, Average Across 3 Waves | 0.25 | 0.82 | 0.30 | 1.34 | 0.975 | .324 |
| Neighborhood-Level Variables | | | | | | |
| Concentrated poverty | –0.12 | 0.72 | –0.06 | 0.74 | 2.501 | .114 |
| % foreign-born | 20.65 | 15.12 | 20.20 | 15.48 | 0.273 | .601 |
| Residential stability | 0.02 | 0.98 | –0.02 | 1.04 | 0.504 | .478 |
| Tolerance of deviance | 0.76 | 0.12 | 0.76 | 0.13 | 1.245 | .265 |
| Collective efficacy | 3.90 | 0.26 | 3.87 | 0.25 | 3.149 | .076 |

*Notes:* $\chi^2$ is the test statistic for comparison of dichotomous measures; the test statistic for all other comparisons is $F(1, 2{,}149)$.

## REFERENCES


Anderson, E. 1999. *Code of the Street*. New York: W.W. Norton & Company.

Blinder, A. 1973. "Wage Discrimination: Reduced-Form and Structural Variables." *Journal of Human Resources* 8:436–55.

Blumstein, A. 1982. "On the Racial Disproportionality of United States' Prison Populations." *Journal of Criminal Law and Criminology* 73:1259–81.

Burton, L. and R. Jarrett. 2000. "In the Mix, Yet on the Margins: The Place of Families in Urban Neighborhood and Child Development Research." *Journal of Marriage and Family* 62:1114–35.

Chambliss, W. and R. Nagasawa. 1969. "On the Validity of Official Statistics: A Comparative Study of White, Black, and Japanese High-School Boys." *Journal of Research in Crime and Delinquency* 6:71–77.

Cook, T.D., S.C. Shagle, and S.M. Degirmencioglu. 1997. "Capturing Social Process for Testing Mediational Models of Neighborhood Effects." Pp. 94–119 in *Neighborhood Poverty,* Vol. II, edited by J. Brooks-Gunn, G.J. Duncan, and J.L. Aber. New York: Russell Sage.

Duncan, G.J. and J. Brooks-Gunn. 1997. *Consequences of Growing Up Poor*. New York: Russell Sage.

Duncan, G.J., J. Brooks-Gunn, and P.K. Klebanov. 1994. "Economic Deprivation and Early-Childhood Development." *Child Development* 65:296–318.

Duncan, G.J. and S.W. Raudenbush. 2001. "Neighborhoods and Adolescent Development: How Can We Determine the Links?" Pp. 10–36 in *Does It Take A Village? Community Effects on Children, Adolescents, and Families,* edited by A. Booth and N. Crouter. Mahwah, NJ: Lawrence Erlbaum Associates.

Hindelang, M.J. 1978. "Race and Involvement in Common Law Personal Crimes." *American Sociological Review* 43:93–109.

Jones, F.L. and J. Kelley. 1984. "Decomposing Differences Between Groups: A Cautionary Note on Measuring Discrimination." *Sociological Methods and Research* 12:323–43.

Kirk, D.S. 2006. "Examining the Divergence Across Self-Report and Official Data Sources on Inferences About the Adolescent Life-Course of Crime." *Journal of Quantitative Criminology* 22:107–29.

Loeber, R. and M. Stouthamer-Loeber. 1986. "Family Factors as Correlates and Predictors of Juvenile Conduct Problems and Delinquency." Pp. 29–149 in *Crime and Justice,* Vol. 7, edited by M. Tonry and N. Morris. Chicago: University of Chicago Press.

Matsueda, R.L., K. Drakulich, and C.E. Kubrin. 2006. "Race and Neighborhood Codes of Violence." Pp. 334–56 in *The Many Colors of Crime: Inequalities of Race, Ethnicity and Crime in America,* edited by R.D. Peterson, L.J. Krivo, and J. Hagan. New York: New York University Press.

McLeod, J.D., C. Kruttschnitt, and M. Dornfeld. 1994. "Does Parenting Explain the Effects of Structural Conditions on Children's Antisocial Behavior? A Comparison of Blacks and Whites." *Social Forces* 73:575–604.

McNulty, T.L. and P.E. Bellair. 2003. "Explaining Racial and Ethnic Differences in Serious Adolescent Violent Behavior." *Criminology* 41:709–46.

Moos, R.H. and B.S. Moos. 1986. *Family Environment Scale Manual*. 2nd ed. Palo Alto, CA: Consulting Psychologists Press.

Oaxaca, R. 1973. "Male-Female Wage Differences in Urban Labor Markets." *International Economic Review* 14:693–709.

Osgood, D.W., B.J. McMorris, and M.T. Potenza. 2002. "Analyzing Multiple-Item Measures of Crime and Deviance I: Item Response Theory Scaling." *Journal of Quantitative Criminology* 18:267–96.

Peterson, R.D. and L.J. Krivo. 2005. "Macrostructural Analysis of Race, Ethnicity, and Violent Crime: Recent Lessons and New Directions for Research." *Annual Review of Sociology* 31:311–56.

Rabe-Hesketh, S., A. Skrondal, and A. Pickles. 2004. "GLLAMM Manual." Working Paper 160. University of California–Berkeley, Division of Biostatistics Working Paper Series.

Raudenbush, S.W. and A.S. Bryk. 2002. *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd ed. Thousand Oaks, CA: Sage Publications.

Sampson, R.J. 1987. "Urban Black Violence: The Effect of Male Joblessness and Family Disruption." *American Journal of Sociology* 93:348–82.

Sampson, R.J. and D.J. Bartusch. 1998. "Legal Cynicism and (Subcultural?) Tolerance of Deviance: The Neighborhood Context of Racial Differences." *Law and Society Review* 32:777–804.

Sampson, R.J. and J.H. Laub. 1993. *Crime in the Making: Pathways and Turning Points Through Life*. Cambridge, MA: Harvard University Press.

Sampson, R.J., J.D. Morenoff, and S.W. Raudenbush. 2005. "Social Anatomy of Racial and Ethnic Disparities in Violence." *American Journal of Public Health* 95:224–32.

Sampson, R.J., S.W. Raudenbush, and F. Earls. 1997. "Neighborhoods and Violent Crime: A Multi-level Study of Collective Efficacy." *Science* 227:918–24.

Sampson, R.J. and W.J. Wilson. 1995. "Toward a Theory of Race, Crime, and Urban Inequality." Pp. 37–56 in *Crime and Inequality,* edited by J. Hagan and R.D. Peterson. Stanford, CA: Stanford University Press.

Shaw, C. and H. McKay. 1942. *Juvenile Delinquency and Urban Areas.* Chicago: University of Chicago Press.

Wells, L.E. and J.H. Rankin. 1991. "Families and Delinquency: A Meta-Analysis of the Impact of Broken Homes." *Social Problems* 38:71–93.

Yun, M.-S. 2004. "Decomposing Differences in the First Moment." *Economics Letters* 82:275–80.